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Research on Aluminum Electrolytic Fault-tolerant Control Strategies Based on Extension Neural Network

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Abstract: Aluminum electrolysis is a complex industrial process with difficult to control and strong interference, where is difficult to make the aluminum electrolytic cell at the best working condition. Consequently, in this study adopted a fault-tolerant control strategy based on extension neural network according to the characteristics of aluminum electrolysis process. The control principle is adopted different control strategies which combined detection and control, made a diagnosis according to the electrolytic cell condition. It was made the aluminum electrolytic cell in the best working state, difficult to control and strong interference optimized the capability of the system such as real-time ability, stability and precision, real-time ability, stability and precision.

Key words: Aluminum electrolysis, fault-tolerant control, extension neural network, detection system, control system

INTRODUCTION

Aluminum electrolytic cell is the core equipment in the aluminum electrolysis process, its operational aspect directly affect on the yield and quality of aluminum. In order to implement the Aluminum electrolysis fault diagnosis more reliable, this study adopt the aluminum electrolytic fault-tolerant control strategies. The network structure was divided into two parts, one part is the aluminum electrolytic cell condition detection system which made a preliminary judgment for the condition of aluminum electrolytic cell; the other part is the aluminum electrolytic cell control system which adopted different control strategies or operation mode for the two different state, namely normal state and faulted state, to make corresponding treatments, finally got the results of the types of failures and the fault diagnosis (Wei and He, 2008; Yu *et al*., 2001)

CONDITION DETECTION SYSTEM

At first the condition detection system made an effective fault prediction for the aluminum electrolysis fault diagnosis and made a preliminary judgment to the condition of the aluminum electrolytic cell. This study adopted the condition detection system based on the extension neural network (Feng, 2006).

The extension neural network has an obvious advantage to solve the problem of classification and recognition based on model which structure design is simple and was able to determine the structure of the extension neural network through the number of input characteristics and output types. This network structure adopted double weighted connection, the weight was an interval rather than a single value, one side represents an upper limit value of the domain; the other side represents a lower limit value of the domain. The physical significance of the weighted connection was clearly, it regarded the aluminum electrolytic cell condition detection as the pattern recognition based on a certain interval.

The first step to diagnose was to choose characteristics which was able to reflect the problem to be solved objectively and comprehensively, in order to achieve the purpose of diagnosing accurately and timely. Through the analysis of the aluminum electrolysis process parameters and the previous study, chose six impact larger parameters as the data samples which are cell resistance, the cell resistance variation, the electrolyte temperature variation, series voltage, electrolyte temperature and the cell voltage variation. Made a preliminary estimate for these original data samples based on GM(1, 1) grey prediction which can weaken the randomness of the data, getting the regularity cumulative

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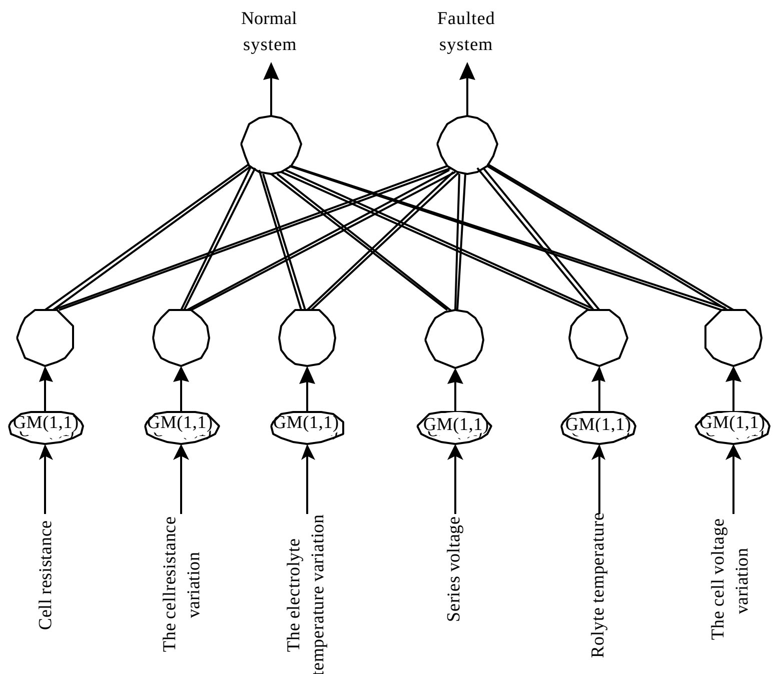

Fig. 1: Aluminum electrolytic cell state detection system based on extension neural network

data as the input characteristics of the extension neural network. This study adopts an extension neural network based on grey prediction double weighted connection to solve the aluminum electrolytic cell condition detection. The system structure was shown in Fig. 1 (Xu *et al*., 2013; Zhang *et al*., 2011).

Input layer: At first made GM(1, 1) estimate for the six original data samples, then taking these outputs, the regularity cumulative data, as the inputs of the feature layer based on extension neural network.

The original sequence defined as follows:

$$x^{(0)} = \{x^{(0)}(1), x^{(0)}(2),\cdots, x^{(0)}(n)\}$$

After an accumulation:

$$x^{(1)} = \{x^{(1)}(1), x^{(1)}(2),\cdots, x^{(1)}(n)\}$$

The first order linear differential equation defined as follows:

$$\frac{dx^{(1)}}{d_t} + ax^{(1)} = u \tag{1}$$

Using least square method to calculate the parameter a, u, the formula as follows:

$$\hat{a} = \begin{bmatrix} a \\ u \end{bmatrix} = (B^tB)^{-1}B^Ty_n \tag{2}$$

$$B = \begin{bmatrix} -\frac{1}{2}(X^{(1)}(1)+X^{(1)}(2)) & 1 \\ -\frac{1}{2}(X^{(1)}(2)+X^{(1)}(3)) & 1 \\ \cdots & \cdots \\ -\frac{1}{2}(X^{(1)}(n-1)+X^{(1)}(N+1)) & 1 \end{bmatrix} \tag{3}$$

The GM(1, 1)grey prediction model of $x^{(1)}$ defined as follows:

$$\hat{x}^{(1)}(k+1) = [x^{(0)}(1) - \frac{u}{a}]e^{-ak} + \frac{u}{a} \qquad (k = 0,1,2,\cdots) \tag{4}$$

Calculated $\hat{x}^{(1)}(k+1)$ through the above equation, the actual prediction value defined as follows:

$$x^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \tag{5}$$

Feature layer: The extension neural network, using the matter element theory made a combination with the fault information based on the extension neural network recovery system, was able to achieve the goal of effective recognition. It used the extension distance of the extension theory as the measure tool to recognize the similarity between the object to be measured and the centre of the distance. The extension distance describes the distance between x and $\langle w_{kj}^L, w_{kj}^U \rangle$, the formula as follows:

$$ED = \frac{|x-z| - (w^U - w^L)/2}{|(w^U - w^L)/2|} + 1 \tag{6}$$

In order to assess the correctness of the extension neural network prediction, N_m represents the total error of prediction, E_T represents the total error rate, the formula as follows:

$$E_T = \frac{N_m}{N_p} \tag{7}$$

The basic learning rule of the network as follows:

- According to the theory of extension matter-element model and the sample data, determining the weights which connected the input and the output, the formula as follows:

$$R_k = \begin{pmatrix} N_k & c_1 & (w_{k1}^L, w_{k1}^U) \\ \vdots & \vdots & \vdots \\ N_k & c_4 & (w_{k4}^L, w_{k4}^U) \end{pmatrix}, k = 1, 2 \tag{8}$$

$$w_{kj} = (w_{kj}^L, w_{kj}^U)$$

The range of the variation, initialized as follows:

$$w_{kj}^L = \mathrm{Min} \sum\nolimits_{i \in N_k} \{x_{ij}^k\} \tag{9}$$

$$w_{kj}^u = \mathrm{Max} \sum\nolimits_{i \in N_k} \{x_{ij}^k\} \tag{10}$$

- Calculated the initial center points of each faulted type:

$$Z_k = \{z_{k1}, z_{k2}, \cdots, z_{kn}\}^{Z_{kj} = \frac{w_{kj}^U + w_{kj}^L}{2}} \tag{11}$$

- Chose the learning samples and the number of the characteristics:

$$X_i^p = \{x_{i1}^p, x_{i2}^p, \cdots, x_{in}^p\} p \in n_c \tag{12}$$

- Used the extension matter-element model theory to determine the initial weight which connected the input and the output, then calculated the initial center points of the each faulted type. Input the training sample i and the corresponding type

The formula of the extension distance between the training sample and the clusters defined as follows:

$$ED_{ik} = \sum_{j=1}^{n} \left[\frac{|x_{ij}^p - z_{kj}| - \left|\frac{w_{kj}^U - w_{kj}^L}{2}\right|}{\left|\frac{w_{kj}^U - w_{kj}^L}{2}\right|} + 1 \right] \tag{13}$$

- Determining k*, setting as$ED_{ik^*} = \min\{ED_{ik}\}$, if k*, go to Step 7 otherwise, go to Step 6
- Updated the corresponding connection weight

The adjustment of the type centre:

$$z_{pj}^{new} = z_{pj}^{old} + \eta(x_{ij}^p - z_{pj}^{old}) \tag{14}$$

$$z_{k^*j}^{new} = z_{k^*j}^{old} + \eta(x_{ij}^p - z_{k^*j}^{old}) \tag{15}$$

The adjustment of the weight:

$$\begin{cases} z_{pj}^{L(new)} = z_{pj}^{L(old)} + \eta(x_{ij}^p - z_{pj}^{old}) \\ z_{pj}^{U(new)} = z_{pj}^{U(old)} + \eta(x_{ij}^p - z_{pj}^{old}) \end{cases} \tag{16}$$

$$\begin{cases} z_{k^*j}^{L(new)} = z_{k^*j}^{L(old)} - \eta(x_{ij}^p - z_{k^*j}^{old}) \\ z_{k^*j}^{U(new)} = z_{k^*j}^{U(old)} - \eta(x_{ij}^p - z_{k^*j}^{old}) \end{cases} \tag{17}$$

- Repeated the step 3-6, the learning step has been completed depends on finished all the samples practicing
- If the classification process has been converged, or the total error rate has reached the target value, it can be stopped, otherwise go to step 3

Output layer: Passed the outputs of the characteristics into the output layer, the output is the result of pattern classification after recognizing, the normal state set as (1, 0), the faulted state set as (0, 1) (Xu, 2009).

CONTROL SYSTEM

The control system was the procedure which is the targeted treatment of the aluminum electrolysis, according to the different working states, adopted different monitor strategies, finally acquire the results. The controller was mainly composed of two parts which were the normal state controller and the faulted state controller.

Normal state control system: In the normal state, the concentration of alumina will decrease with the process of the aluminum electrolysis, needed to add alumina into the

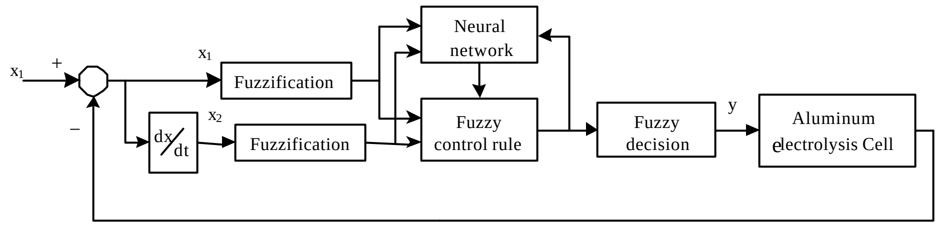

Fig. 2: Principle diagram of the aluminum electrolytic cell control system based on normal state

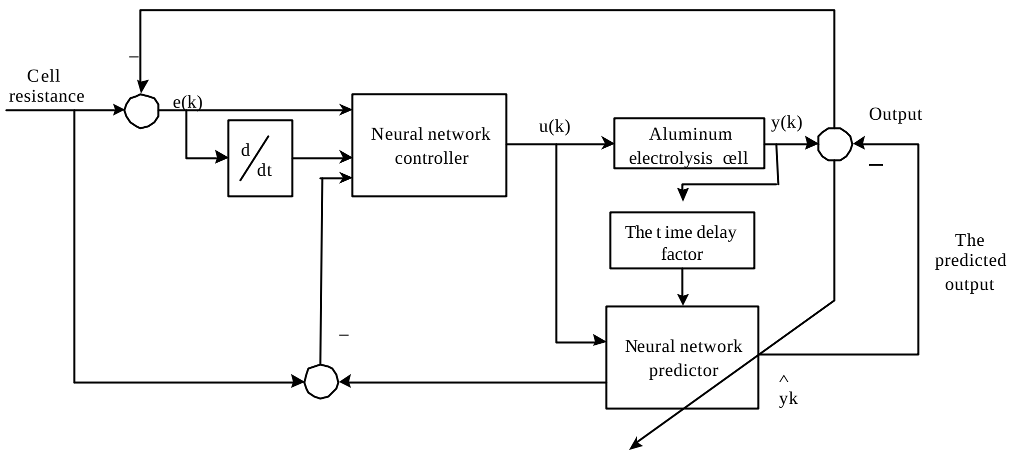

Fig. 3: Principle diagram of the aluminum electrolytic cell control system based on faulted state

electrolytic cell, to control the time and the speed of adding materials. According to the characteristics of the aluminum electrolysis, this study adopts the fuzzy RBF neural network control method. The principle diagram of the aluminum electrolytic cell control system based on normal state was shown in Fig. 2 (Pan *et al*., 2012).

The method utilized the function equivalence between the fuzzy inference system and the RBF neural network which to unify the system based on the functions, it has a good effect in the control of the complex nonlinear and the uncertainty system, with a better logical reasoning and adaptive ability.

Faulted state control system: Aluminum electrolysis is a complex industrial process, once a fault occurs, it could changed the temperature of electrolytic cell obviously which the dynamic rule was different from the normal state such as the aluminum liquid and the process parameter fluctuate obviously. In this study adopted the predictive control strategies based on neural network, through predicting the future parameters, adjusted the control strategy of the controller in the real-time which was able to adapt to the changing law of the failures and reached the better control performance in the faulted state. In order to retain the alumina concentration in a certain range, making a real-time control for it. Owing to the alumina concentration couldn't monitor on-line, it related to the cell resistance and the change rate of cell resistance, as a result controlled the concentration of alumina indirectly by controlling the cell resistance and other parameters (Ma *et al*., 2012).

The aluminum electrolytic cell control system based on faulted state was mainly composed of two parts which were the controller and the predictor. The inputs respectively are cell resistance and the change rate of cell resistance. The input of the controller is the cell resistance x(k), the output y(k) is the actual output of the cell resistance, the output u(k) of the neural network controller served as the input of the recursive wavelet neural network prediction structure, the output $\hat{y}(k)$ of the predictor served as the parameters back to the controller, in order to improve the control precision of the system. The principle diagram of the aluminum electrolytic cell control system based on faulted state was shown in Fig. 3.

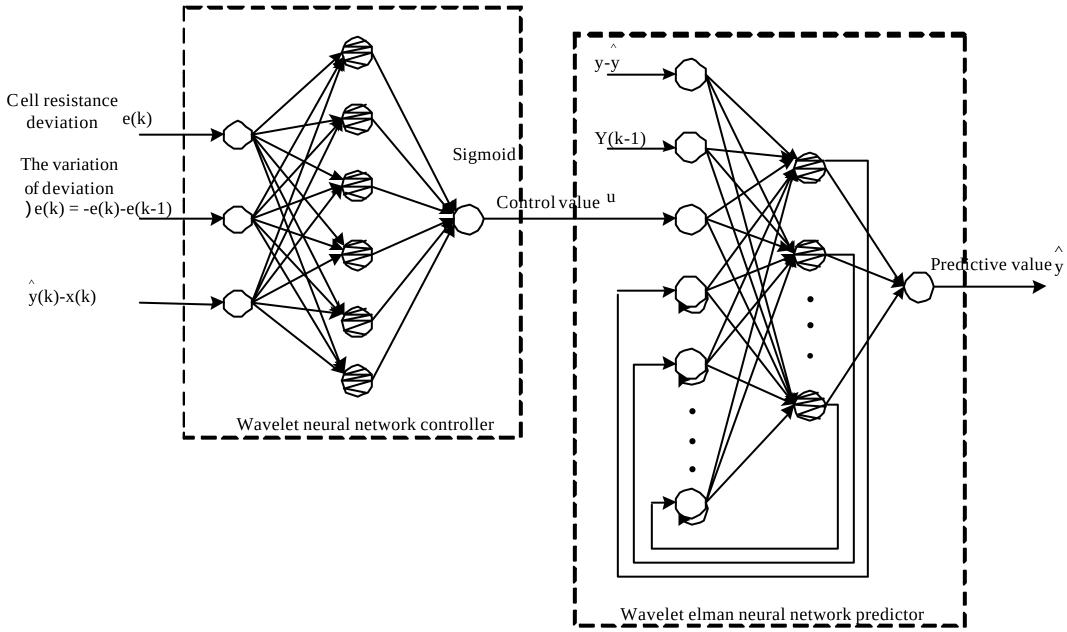

Fig. 4: Structure diagram of the aluminum electrolytic cell control system based on faulted state

The predictor adopted wavelet Elman neural network. The structure diagram of the aluminum electrolytic cell control system based on faulted state was shown in Fig. 4.

Wavelet neural network controller: Respectively calculate the total input and output of the hidden layer nodes and the output nodes. Get the following formulas:

$$X_h^p = i = \sum_{i=1}^{I} (w_{hi} * x_i^p) + \phi_h \quad (18)$$

$$X_o^p = \sum_{k=1}^{H} (w_{oh} * Y_k^p) + \phi_o \quad (19)$$

$$Y_h^p = f_H(X_h^p) = \psi(\frac{X_h^p - b_h}{a_h}) \quad (20)$$

$$\dot{Y}_h^p = f_H{}'(X_h^p) = \psi'(\frac{X_h^p - b_h}{a_h}) \quad (21)$$

$$Y_o^p = f_O(X_o^p) = \frac{1}{1 + e^{-X_o^p}} \quad (22)$$

The total error energy function defined as follows:

$$E = \frac{1}{2}\sum_{p=1}^{P}\sum_{o=1}^{O}(Y_o^p - \tilde{Y}_o^p)^2 = \frac{1}{2}\sum_{p=1}^{P}(Y_o^p - \tilde{Y}_o^p)^2 = \frac{1}{2}\sum_{p=1}^{P} e^2 \quad (23)$$

Wavelet elman neural network predictor: The mathematical model of the wavelet Elman neural network:

$$x_c(k) = \alpha xc(k\text{-}1) + x(k\text{-}1) \quad (24)$$

$$x(k) = \psi(\frac{h(k) - b_i(k)}{a_i(k)}) \quad (25)$$

$$y(k) = gW^3(k)x(k)) \quad (26)$$

$$h(k) = W^1(k)x_c(k) + W^2(k)u(k) \quad (27)$$

$$X = \frac{h(t) - b_i(t)}{a_i(t)} \quad (28)$$

The Morlet wavelet defined as follows:

$$\psi(X) = \cos(1.75X)e^{-\frac{X^2}{2}} \quad (29)$$

$$y(k) = g(W^3(k)x(k)) \quad (30)$$

The error function:

$$E(k) = \frac{1}{2}(y_d(k) - y(k))^T(y_d(k) - y(k)) \quad (31)$$

SIMULATION

In order to verify the rationality of the control strategies, the simulation experiment was carried out. The cell resistance comes from the following calculation method:

$$R = \frac{V_{iE} - E}{I_c}$$

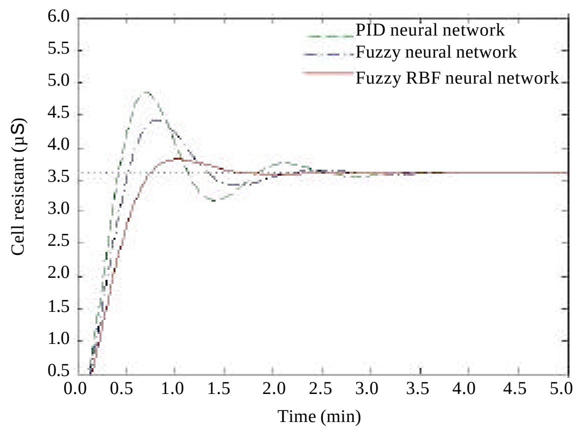

Fig. 5: Control system simulation diagram based on normal state

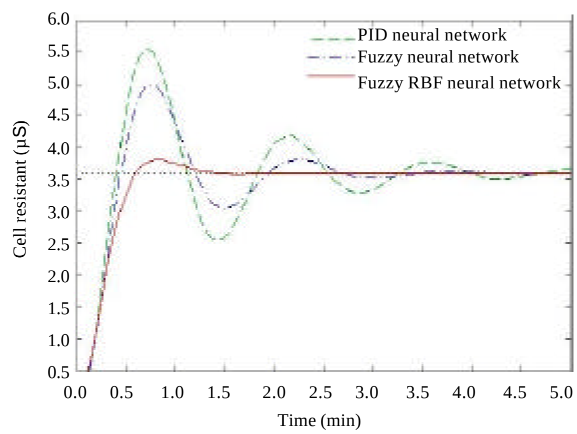

Fig. 6: Control system simulation diagram based on faulted state

The system after extension neural network detect, the simulation diagram of the normal state control system and the fault state control system are shown in Fig. 5 and 6, respectively.

From the simulation diagram we can reasonably come to the conclusion: The system after extension neural network detect, adopt the fuzzy RBF neural network control system adjust the time about 1.3 minutes earlier than the PID control, about 2 minutes earlier than the fuzzy neural network. What's more, it has a fast response rate, hardly any overshoot, a smaller steady-state error and Early finished control requirements into the steady state.

From the simulation diagram we can reasonably come to the conclusion: The system after extension neural network detect, adopt the wavelet fuzzy neural network control will decreased the oscillation amplitude which has the shorter vibration time, the more accurate control precision, the better adaptive ability and robustness.It can meet the real-time requirements.

Consequently, based on the above analysis, the fault-tolerant control strategies that first for detection and followed by control in different condition respectively. It is used in the aluminum electrolysis fault diagnosis system which is nonlinear and multi-variable, improved its diagnostic accuracy greatly and reached the actual demand.

CONCLUSION

The fault-tolerant control strategies in this study, compared with other control methods, had a stronger adaptive ability and a better control effect which are safe and reliable. It is applied to aluminum electrolysis fault diagnosis system which can acquire the most effective ways to improve its steady-state and dynamic performance, highly control precision, making the aluminum electrolytic cell in the best state. It implements the optimization control based on aluminum electrolysis process, thus deserves to be widely applied.

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